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A hybrid process based-empirical approach to identify the association between wheat productivity and climate in the North China Plain during the past 50 years☆

Ruirui Zhu[a,c,*], Hongxing Zheng[b], Enli Wang[c], Anthony J. Jakeman[a]

[a] Fenner School of Environment and Society, Australian National University, Canberra, ACT, 0200, Australia
[b] CSIRO Land and Water, Canberra, ACT, 2601, Australia
[c] CSIRO Agriculture, Canberra, ACT, 2601, Australia

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ABSTRACT

China is anticipated to face reductions in crop yield due to climate change. Combining a process-based agricultural model (APSIM) with a simplified empirical model, we investigate the association between wheat productivity and climate variables in the North China Plain (NCP) over the period 1960–2010. The results show that the spatial distribution of wheat productivity across NCP is negatively related to daily maximum temperature but positively to daily minimum temperature, solar radiation and precipitation. For most parts of the NCP, partial correlation analysis based on the APSIM simulation outputs indicates that the increasing daily minimum temperature could lead to higher productivity but the effects are counteracted by increases in daily maximum temperature. In the drier northern NCP, wheat productivity is largely discounted due to decreases in precipitation, while in the humid southern edge of the NCP, the productivity stimulation effect of warming is offset by dimming.

Software availability

- Name of software: Agricultural Production Systems Simulator (APSIM)
- Developer: APSIM Initiative
- Contact address: 203 Tor Street, Toowoomba, Qld 4350, Australia • Telephone: +61 7 4688 1596 • Email: apsim@daff.qld.gov.au
- Year of first available: 1994
- Hardware required: Any recent PC with a minimum of 2 Gb of RAM, 32 or 64 bit
- Software required: Windows XP, Vista, Windows 8 or Windows 10/ Mono 2.10 for Linux
- Availability: https://www.apsim.info/
- Cost: free for non-commercial use.

1. Introduction

Food security is one of the largest global concerns with regard to the impact of global climate change (Beddington et al., 2012; Campbell et al., 2016; IPCC, 2014; Lobell and Asseng, 2017). All of the four dimensions of food security (i.e. availability, accessibility, utilization and stability) could be affected by climate change directly or indirectly (Battisti and Naylor, 2009; FAO, 2008; Godfray et al., 2011; Lesk et al., 2016; Rosenzweig et al., 2014; Tai et al., 2014; Wheeler and von Braun, 2013). The effects of climate change on crop and food production are becoming evident in a number of regions around the world and showing more commonly to be negative than positive, although the negative impacts of climate change could be offset by the effect of CO_2 fertilization to some extent (e.g. Betts et al., 2007; Gedney et al., 2006; Lobell et al., 2011; Long et al., 2006; Porter et al., 2014). It is reported that, due to climate change, agriculture output in developing countries may decline by 20% on average by 2080, while agriculture output in industrialized countries is expected to decrease by 6% (FAO, 2008). Among the countries most affected by climate change, China is anticipated to face more frequent extreme weather events like droughts and floods, which could result in the reduction of crop yields. In addition, with the increasing food demand due to a growing population and rising living standards, food security in China may become more challenging; and the international grain markets could be deeply reshaped as China is the world's largest wheat producer and consumer

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* Corresponding author. Fenner School of Environment and Society, Australian National University Building 48A, Linnaeus Way, Canberra, ACT, 0200, Australia.
E-mail address: Ruirui.Zhu@anu.edu.au (R. Zhu).

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(Godfray et al., 2010; IPCC, 2014; Piao et al., 2010; Turral et al., 2011; Zhang et al., 2013).

As a pivot subject of climate change mitigation and adaptation, the responses of crop yields to climate change have been investigated in numerous research articles, many of which have come up with important conclusions showing the association between crop production and climate change (e.g. Asseng et al., 2013, 2015; Battisti and Naylor, 2009; Butler and Huybers, 2013; Conway et al., 2014; Lobell et al., 2011; Urban et al., 2015; Wheeler and von Braun, 2013). In general, a 1 °C rise in temperature could lower crop yields by up to 10% except in high-latitude regions (Lobell et al., 2011). For high-latitude regions like Scotland, however, the measured warming could contribute more than 20% of the increased crop yields over the period 1960–2006 (Gregory and Marshall, 2015). Based on a meta-analysis of around 1700 model simulations, the most recent IPCC assessment demonstrated that, on average, global mean crop yields (i.e. rice, wheat and maize) are projected to decrease between 3% and 10% per degree of warming above historical levels (Challinor et al., 2014), among which the global wheat reduction rate is estimated to be 6% per degree of warming (Asseng et al., 2015).

For the response of crop yield to precipitation change, the yields of nearly all crops show a positive relationship with precipitation but could be undermined by flooding and water-logging caused by extremely high precipitation events (Falloon and Betts, 2009; Lobell et al., 2011). Many of the largest falls in crop productivity have been attributed to anomalously low precipitation events (Kumar et al., 2004; Sivakumar et al., 2005). Indeed crop yield is quite sensitive to precipitation. Lobell and Burke (2008) estimated that a one standard deviation change in precipitation in the growing season could lead to about a 10% change in millet production in South Asia. Additionally, research has also shown that decline in solar radiation and change in radiation composition could have significant effects on plant growth and crop productivity (Chameides et al., 1999; Rodriguez and Sadras, 2007; Swain et al., 2007; Wild et al., 2012).

When investigating the association between crop productivity and climate change, agricultural models are often used (Challinor et al., 2014; Cohn et al., 2016; Holzworth et al., 2015; Lobell and Burke, 2010; Lobell et al., 2011; Rosenzweig et al., 2014). Such agricultural models, which represent mathematically the relations between crop productivity and climate variables, could be strongly process-based (e.g. APSIM, EPIC, CERES and DSSAT, etc.) or simplified statistical ones (e.g. Asseng et al., 2011; Challinor et al., 2014; Chen et al., 2010; Liu et al., 2010; Lobell and Burke, 2010; Piao et al., 2010; Ray et al., 2015; Tao et al., 2012; Wang et al., 2012). The process-based model type has advantages in characterizing the dynamics of crop growth and development in sufficient detail and being able to evaluate the effects of climate change on crop yield when it is well calibrated (Lobell and Burke, 2010; Lobell and Asseng, 2017; Wilcox and Makowski, 2014). However, the process-based model requires routine meteorological inputs like precipitation, temperature, solar radiation, relative humidity, etc. It becomes difficult if not impossible for the application of the model when faced with limited inputs. Moreover, since the process-based model usually operates at a daily time step while crop yield is output as an annual total, the relations between crop yield and climate factors are not explicitly shown at annual scale but require additional efforts to be identified (Lobell and Asseng, 2017; Peng et al., 2004).

In contrast, the statistical model type is easily applicable and can directly summarize with less effort the relationship between crop yield and climate factors at an annual scale, which is practicable for farm planning and decision-making under changing climate (Deryng et al., 2011; Lobell and Asseng, 2017; Makowski et al., 2015; Wilcox and Makowski, 2014). However, the statistical relations between crop yield and climate variables for most of the statistical models are set up based on crop yield census data, which could be at a regional average scale and mismatched in space with the climate observations. The relations can be further confounded as the measured crop yield could also be affected by other factors (e.g. changes in cultivars, agronomic management practice and technological advancement) not represented in the statistical model. To enhance the reliability of the statistical model, improved crop production datasets and novel approaches are needed to better understand the association between crop yield and climate (Lobell et al., 2011; Schlenker and Roberts, 2009; Welch et al., 2010).

In China, both the process-based and the statistical model types have been used to assess the impact of climate change on crop production (e.g. Chen et al., 2010; Liu et al., 2010; Piao et al., 2010; Tao et al., 2006, 2012; Wang et al., 2009, 2012; Xiao et al., 2012). It has been reported that rising temperatures since the 1980s have negatively affected crop production in the North China Plain. This has arisen because of the shortening of the length of the crop growth period, accelerating the physiological development rate and diminishing the growth duration and rate of photosynthesis and biomass accumulation (e.g. Liu et al., 2010; Porter and Gawith, 1999; Tao et al., 2012; Xiao et al., 2012; Zhang et al., 2013). Meanwhile, declining solar radiation and precipitation have further reduced crop yields in the North China Plain (Chen et al., 2010; Tao et al., 2012; Yang et al., 2013). However, the spatial association between crop yield and climatic variables remains inconclusive and the response of crop yield to each climate variable is not yet well understood (Liu et al., 2010; Lobell et al., 2011; Olesen et al., 2011; Tao et al., 2012).

In this paper, we aim to investigate the association between winter wheat productivity and climate variables across the North China Plain (NCP) for the period 1960 to 2010. The process-based agricultural model APSIM (Agricultural Production Systems Simulator) is used firstly to simulate wheat productivity. On the basis of APSIM simulations, a statistical model is then developed to reflect explicitly the underlying climate factors shaping the spatial distribution of wheat productivity. It is used as a surrogate of the APSIM model to estimate wheat productivity where daily meteorological inputs are not available. Thereafter, the relation between wheat productivity and climate factors for each site is further investigated to define the dominant climate factor affecting wheat productivity changes across the North China Plain during the period 1960 to 2010.

2. Data and methods

2.1. Study area

The North China Plain (NCP) is known as the barn of China, contributing 50% of the nation's total wheat production (Liu et al., 2010; Jeong et al., 2014). Located at 31°42′-40°30′N and 110°24′-122°42′E, it covers seven provinces in China (Fig. 1). The NCP has a warm, temperate monsoon climate with great seasonal and annual variation in temperature and precipitation, where winter is cold and dry but summer is hot and wet. The observed mean daily temperature in the region varies from 10.7 °C in the north to 15.6 °C in the south. Mean annual precipitation ranges from 478 mm in the northwest to 1114 mm in the southeast. Farmland accounts for 72% of total land area in the NCP, of which around 82% is irrigated. Water shortage in the NCP is an important constraint on the cropping system. Increasing evidence suggests that climate change in the NCP (e.g. higher temperature, less solar radiation and precipitation) has adverse impacts on the cropping system (Chen et al., 2010; Liu et al., 2010; Lobell et al., 2011; Ray et al., 2015). In addition, shrinking farmland as a consequence of urbanization makes it more challenging to meet the increasing food demand (Yue et al., 2010).

2.2. Climate and phenology data

To investigate the association between winter wheat yield and climate, daily meteorological datasets provided by the China Meteorological Administration are used. The dataset includes daily air temperatures (maximum and minimum), precipitation and sunshine

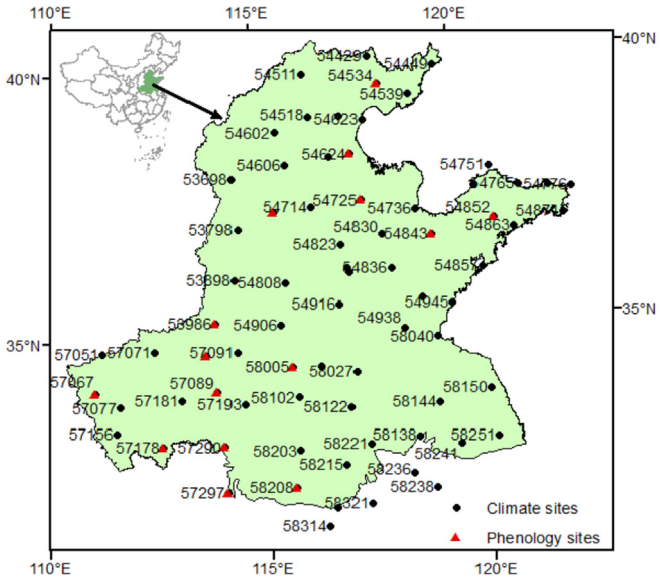

Fig. 1. Sketch map of North China Plain with locations of meteorological and phenology observation sites.

hours for 73 stations in the NCP over the period 1960 to 2010. Solar radiation observations, one of the required inputs to APSIM, are calculated from sunshine hours by using the Angstrom equation (Angstrom, 1924). Among the 73 meteorological sites, 15 sites have phenology observations, which are used to evaluate the performance of APSIM model. The phenology dataset includes sowing date, emergence date, jointing date and maturity date of winter wheat for the period 1991 to 2010 (e.g. Xiao et al., 2012).

2.3. Methods

APSIM (Agricultural Production Systems Simulator), developed by the Agricultural Production Systems Research Unit in Australia, is a daily process-based model of agricultural systems (Holzworth et al., 2014; Keating et al., 2003). It can simulate the growth and yield for many crop species in response to climate and management conditions, and predict the long-term consequence of cropping systems on soil physical and chemical conditions (Keating et al., 2003). It has been widely used and validated in Australia, China, the United States and Africa. Research indicates that the APSIM model simulates very well wheat growth, yield and water consumption in the NCP (e.g. Chen et al., 2010; Li et al., 2014; Xiao and Tao, 2014; Wang et al., 2009, 2012; Zhang et al., 2012).

In this study, the APSIM model version 7.6 is used to simulate rainfed winter wheat growth in the NCP. The minimum required climatic inputs include daily maximum (T_{max}) and minimum (T_{min}) temperature, radiation (Rad) and precipitation (P). As described in the APSIM-Wheat module, there are seven parameters that need to be determined (Table 1). The seven parameters not only control phenology development of winter wheat but also influence biomass accumulation and harvested grain. Among them, parameters $P_1 \sim P_4$ are mainly related to wheat phenology while parameters $P_5 \sim P_7$ are associated with yield. The larger the values of P_1 and P_2, the more sensitive the cultivar is to vernalization and photoperiod. Cultivars with high P_1 and P_2 are a strong winter variety, requiring more vernalization days. Parameters P_3 and P_4 are required thermal duration of the phase from grain filling to maturity and from emergence to end of juvenile, respectively. Higher values of P_3 and P_4 suggest that a crop would go through the grain filling stage and juvenile stage much more slowly. More details of the APSIM model can be found at the website (https://www.apsim.info).

Generally, the parameters are calibrated by using field observations to optimize APSIM model performance with a trial-and-error method (Li et al., 2014; Xiao and Tao, 2014; Zhang et al., 2012). In the calibration procedures, usually the parameters for phenology development are determined first and then the parameters for grain development. Proper simulation of phenology is the first priority to calibrate the crop model since phenology captures much of the genotypic variation and drives many crop-related processes in simulation models (Archontoulis et al., 2014). The proper simulation of crop phenology is a necessary condition for the crop model to produce reliable estimation of biomass production and grain yield (Robertson et al., 2002). If the model performs well in simulating phenology, it is usually expected to have strong potential to provide reliable yield predictions. The model can also be calibrated against observed wheat yield when the aim of the study is to simulate actual productivity for given environmental and management conditions. However, since this study focuses on the changes in wheat productivity from climate, it is not essential to compare the climatic productivity against the actual one.

In this study, different to the trial-and-error method, the parameters are determined based on parameter candidates selected via literature review. The candidates are selected in accordance with the principles of representativeness, reliability and reproducibility. As shown in Table 1, there are eight parameter candidates applicable for winter wheat simulation across the NCP. It is worth noting that the parameter set is cultivar dependent, which means that the parameter set could not be the same for different cropping sites. However, since the scope of this study focuses on the association between crop yield and climate variables only, to remove the effect of the difference in cultivar, we assume the cultivar is the same for all sites across the NCP. Therefore, the parameter set should be identical for all sites as well. The single parameter set suitable for all sites in the region is then selected from the eight candidates according to their overall performance at the 15 sites against phenology observations available.

In setting-up of the APSIM-wheat module in this study, the sowing date is assumed to be the date when there are three continuous days with daily mean air temperature lower than 18 °C (Mo et al., 2009). The simulations also assume that soil texture of the whole study area is uniform and with sufficient fertilizer inputs, thus neglecting the differences in soil physical and chemical properties like water-holding capacity, soil water infiltration, root penetration, soil aeration and soil salinization. The soil up to a 1.5 m beneath the surface is divided into six layers and values of soil properties for each layer are set according to the results of Zhang et al. (2012). As we focus on the climatic productivity of winter wheat, to eliminate the impacts of other environmental and management factors, the cropping system in the region is assumed to be wheat-only though wheat-maize rotation is more common. The model runs continuously for the simulation period, but different to the simulation of wheat-maize rotation cropping, it assumes that there are no planting activities at the growing season of maize. Thereafter, consecutive simulations of winter wheat productivity are conducted for all 73 stations across the NCP over the period 1960–2010.

3. Results and discussions

3.1. Performance of APSIM-wheat module

Fig. 2 shows the performance of APSIM wheat modelling for the 15 phenology sites using all of the eight parameter candidates. Measures of performance invoked (see Bennett et al., 2013) were the determination coefficient (R^2) and root mean square error ($RMSE$), calculated according to simulated and observed dates of maturity for 1990–2010. As seen from Fig. 2, in general, simulated and observed dates of maturity agree well for all 15 sites. The differences ($RMSE$) between simulated and observed dates of maturity for the eight parameter candidates range from 3.38 to 5.15 days at all 15 sites but average at 4.20 days. The determination coefficient (R^2) is about 0.44–0.64 with an average

Table 1
Parameter candidates of APSIM-Wheat module across the NCP. The parameters P_1, P_2, P_3, P_4, P_5, P_6 and P_7 are sensitivity to vernalization (vern_sens), sensitivity to photoperiod (photop_sens), thermal time from beginning of grain-filling to maturity (startgf_to_mat), thermal time from emergence to end juvenile stage (tt_end_of_juvenile), kernel number per stem weight at the beginning of grain filling (grains_per_gram_stem), potential grain filling rate (potential_grain_filling_rate) and potential maximum grain size (max_grain_size), respectively.

Cultivar	Parameter							Sources
	P_1	P_2	P_3 (°C·d)	P_4 (°C·d)	P_5 (g/stem)	P_6 (g/kernel/day)	P_7 (g/kernel)	
Nongda211	3.4	3.2	540	400	27	0.0028	0.041	Zhang et al. (2012)
Han6172	3.2	3.3	560	400	33	0.0025	0.041	Zhang et al. (2012)
Yanzhan4110	2.9	3.3	550	400	33	0.0028	0.041	Zhang et al. (2012)
Lumai21	3.0	3.1	570	400	30	0.0032	0.041	Li et al. (2014)
Tangshan00	1.6	2.0	630	660	26	0.0025	0.045	Xiao and Tao (2014)
Nangong00	1.6	2.0	650	590	25	0.0025	0.042	Xiao and Tao (2014)
Zhumadian00	1.6	2.0	600	600	27	0.0025	0.046	Xiao and Tao (2014)
Huimin00	1.7	2.0	590	620	28	0.0025	0.046	Xiao and Tao (2014)

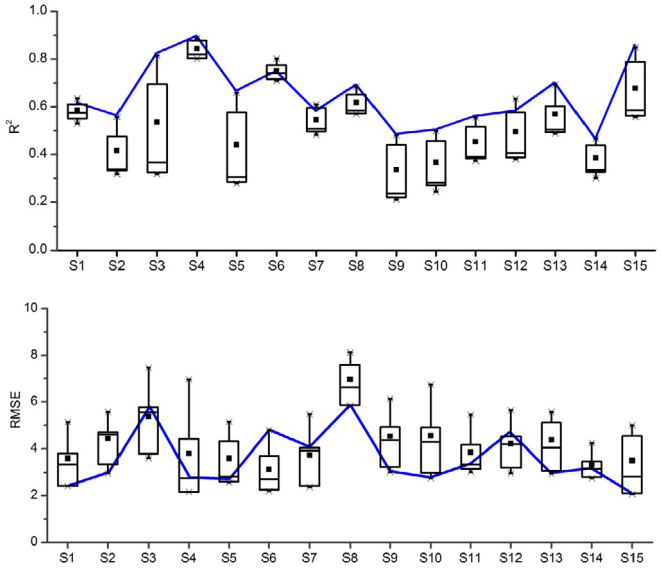

Fig. 2. Model performances across the 15 phenology sites. Horizontal axis represents sites. The line represents simulation performance of the selected parameter set, while the box plot shows the range of the evaluation metrics for the simulations based on all the eight parameter sets, in which the mean (the dot), 1st, 25th, 50th, 75th, and 99th percentiles are presented.

of 0.53 for all 15 sites and there are nine sites with an R^2 greater than 0.5 (up to 0.84). Comparably, the overall performance of the parameter candidates relative to cultivar Nongda211 (see Table 1) is the best for its higher R^2 (about 0.48–0.89 with an average of 0.66) and lower *RMSE* (about 2.05–5.84 days with an average of 2.97 days) for most of the sites.

Fig. 3 further shows the range of ensemble simulations of the rain-fed wheat productivity using all the eight parameter candidates. It shows clearly that simulations from different parameter candidates are not distributed uniformly for a specific year as the median could be quite different to the mean. The range of the ensemble simulations varies among the simulation periods. For some years, the performance among the different parameter candidates is quite consistent (smaller range). It is worth noting that there is no systematic underestimate/overestimate of wheat productivity for a specific parameter set as compared against the others, which means that the simulated productivity of a parameter set may be lower than the other parameter sets in a specific year, but it is not necessarily lower in the other years. The results mean that the productivity of different cultivar varies with climate condition. To maximize wheat productivity, it implies that it could be beneficial to change the cultivar in adaptation to climate variation. Actually, wheat cultivar in the NCP has been renewed about every 3–5 years and approximately 347 cultivars were released and introduced into the national seed market in China from 1984 to 2010 (Xiao and Tao, 2014). Those crop cultivars have different genetic characteristics and hence their response and adaption to climate change are distinct. Existing research suggests that cultivar renewal and improved crop management practices have offset negative effects of climatic change on crop yields (Liu et al., 2010; Tao et al., 2012; Wang et al., 2012).

As shown, the response of crop yield to climate varies among cultivars. To demonstrate the responses of wheat productivity to climate conditions across the NCP, for simplification, the parameter set for cultivar Nongda211 is selected in this study. It is applied for all sites across the NCP because it provides the overall best phenology simulation (Fig. 2), and is much closer to the median productivity simulations based on all the parameter candidates (Fig. 3).

3.2. Spatial variation of wheat productivity in association with climate

Fig. 4 presents the spatial variation of the mean winter wheat

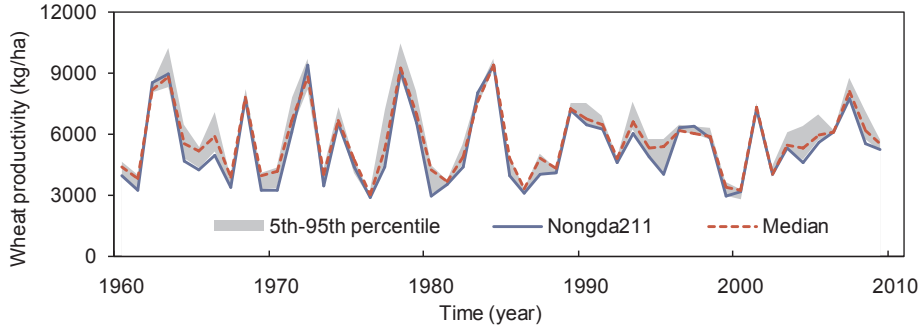

Fig. 3. Simulated rain-fed wheat productivity (at the site 54916) using different parameter sets for the period 1961 to 2010. The solid line is the result for the Nongda211 parameter set. The dashed line is the median of all simulations. The grey shadow is the 5th-95th percentile range of the simulations.

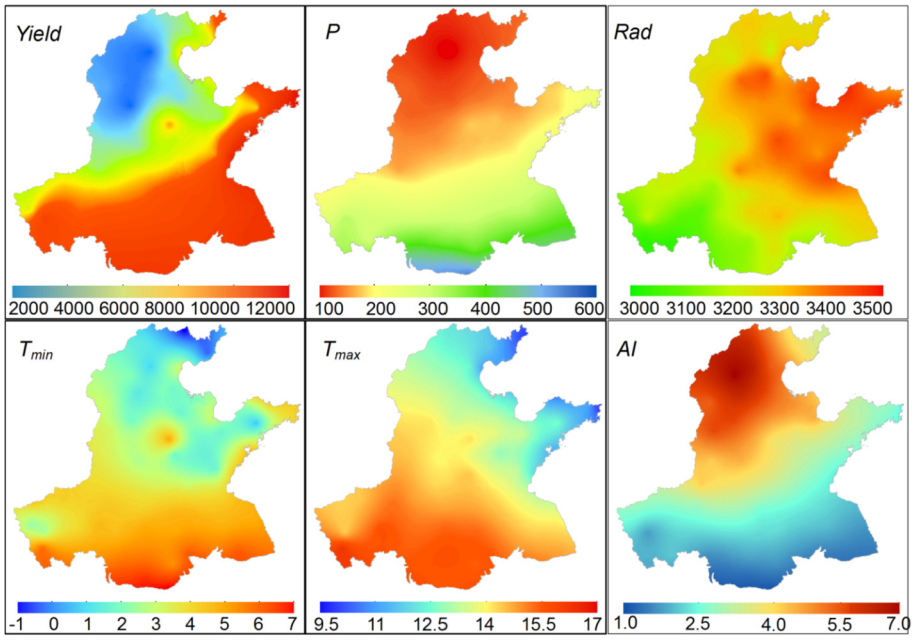

Fig. 4. Spatial patterns of winter wheat productivity and growing-season climate factors for the period 1960–2010.

productivity under the rain-fed condition for the period 1960 to 2010. In general, the annual wheat productivity (*Yield*) decreases from 11575 kg/ha in the southeast to 2868 kg/ha in the northwest. The high productivity area (i.e. *Yield* > 6000 kg/ha) accounts for 49.06% for the total farmland area in the NCP, while the relatively low productivity area (i.e. *Yield* < 3000 kg/ha) is about 11.76% of the total farmland area. To estimate the regional mean productivity, based on the simulations of the 73 sites, we use the Kriging method to estimate the productivity of each farmland pixel at the resolution of 1 km × 1 km. The result shows that the mean regional productivity of the NCP is around 6673 kg/ha and coefficient of variation is 0.33.

Fig. 4 also shows the spatial pattern of the climate variables closely related to wheat cropping, where *AI* is the aridity index, being the ratio of potential evapotranspiration to precipitation. From the southeast to the northwest of the NCP, there is a clear decrease in precipitation but an increase in *AI*. Meanwhile, both T_{min} and T_{max} increase from north to south but *Rad* gradually intensifies from the southwest to the northeast. Comparing the spatial patterns of wheat productivity in the NCP, it is found that the rain-fed productivity is highly related to precipitation; where there is higher precipitation it tends to have higher productivity. The lowest wheat productivity is found in places with the highest *AI* (greater than 5.5) while the highest wheat productivity is at the lowest *AI*. Productivity is also affected by available solar radiation (*Rad*) and temperature in the actual growing season. In the north, winter wheat growth is often stressed by frost damage and less precipitation, and hence productivity is lower. In contrast, in the south, more precipitation and higher temperatures provide sufficient water and heat resources for wheat growth and grain formation and hence bring about higher wheat productivity. It is recorded that across the NCP, wheat is typically planted in late autumn and harvested in early summer (Xiao et al., 2012). Growth of winter wheat in the NCP is often stressed by low temperature and less precipitation. Low temperature especially in the north often leads to frost damage, which could affect wheat growth and may even kill wheat plants in winter and early spring (Jin, 1996). Drought stress is another important climate condition affecting growth, development and production of plants in the NCP (Chen et al., 2010). Water deficit before anthesis may lead to a loss in yield by reducing spike and spikelet number and the fertility of surviving spikelets. After anthesis, water deficit, especially if accompanied with high temperatures, could hasten leaf senescence, reduce grain-filling rate and hence reduce mean kernel weight and dry matter accumulation (Giunta et al., 1993; Royo et al., 1999).

To further investigate the spatial association between rain-fed wheat productivity and climate condition across the NCP, stepwise regression was implemented to represent the relationship between crop yield and related climate factors, where the crop yield used is from the simulation from APSIM. The regression analysis is based on the simulated crop yield from APSIM, where all dependent and independent variables are standardized by the correspondingly maximums to eliminate the effects of dimension. The regression analysis is valuable to identify the dominant climate variables affecting the spatial pattern of crop yield. The result shows that the annual wheat productivity of a specific site is a function of annual precipitation and solar radiation, and mean daily minimum and maximum temperature of the actual growing season, which can be expressed as:

$$K_y = 2.31 \times K_p - 1.54 \times K_p^2 + 0.45 \times K_{rad} + 0.36 \times K_{tmin} - 0.76 \times K_{tmax} - 0.013 \quad (1)$$

where K_y is standardized wheat productivity; K_p and K_{rad} are standardized total precipitation and radiation of the actual growing season, while K_{tmin} and K_{tmax} are standardized mean daily minimum and maximum air temperature in the actual growing season. The regression function is at a confidence level of 99%. The correlation coefficient between simulated wheat productivity from APSIM and the regression model reaches 0.96 (Fig. 5).

The regression model (Eq. (1)) indicates that the dominant climate factors for wheat productivity in the NCP are precipitation, solar radiation, and daily minimum and maximum air temperature. According to the regression model, it can be seen that, spatially, a non-linear effect exists between rain-fed wheat productivity and precipitation, implying that crop yield is not necessarily increasing/decreasing with increase/decrease in precipitation. It is easy to derive from Eq. (1) that the partial derivative of wheat productivity to precipitation is given as:

$$G_p = \frac{\partial K_y}{\partial K_p} = 2.31 - 3.08 \times K_p \quad (2)$$

where G_p represents the spatial gradient of rain-fed wheat productivity against precipitation (P). It is obvious that G_p is not a constant but depends on K_p. G_p decreases with increasing K_p, which implies that for drier regions the gradient is larger than for wetter regions. Moreover, G_p

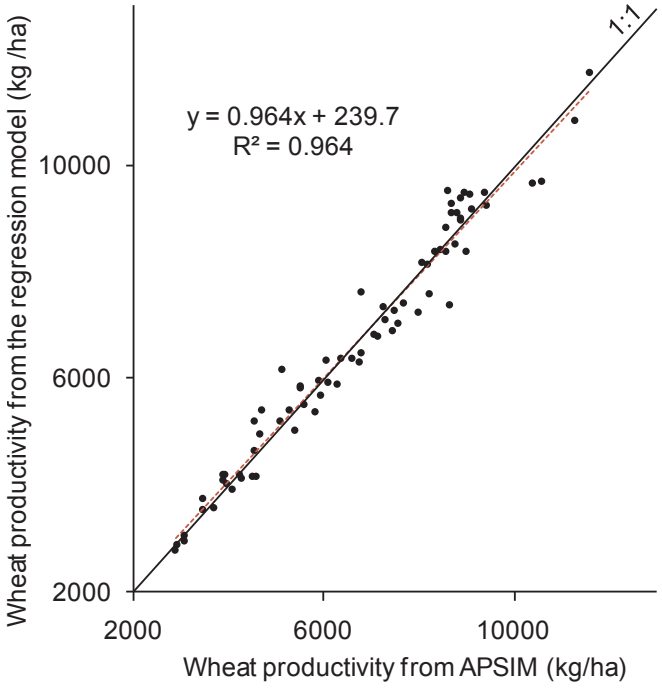

Fig. 5. Relationship between annual mean wheat productivity simulated by APSIM and that from the regression model.

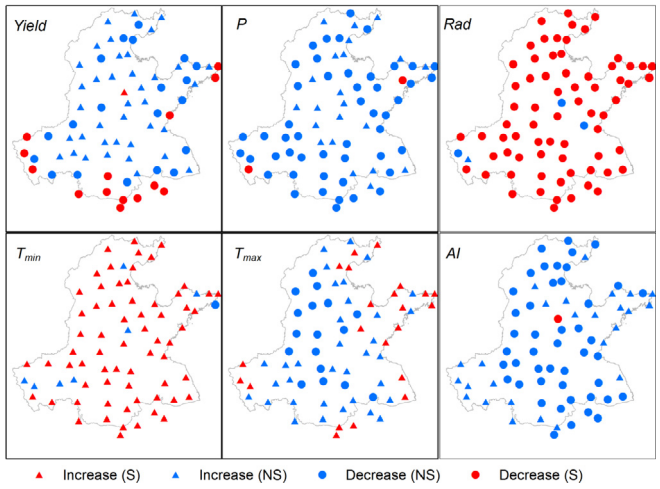

Fig. 6. Long-term change in wheat productivity and growing-season climate factors during 1960–2010 in the NCP. Triangles represent increasing trends while circles represent decreasing trends. Red circles (or triangles) represent trends that are statistically significant (S) and blue circles (or triangles) indicate insignificant trends (NS). The significance level adopted is 0.05.

can also be negative if K_p is higher than 0.75, implying a negative effect of higher precipitation on wheat productivity in the humid region (where precipitation in the wheat growing season is higher than 195.5 mm). As seen from Eq. (1), the spatial gradient (represented by partial derivative and equal to the regression coefficient) of wheat productivity against *Rad*, T_{max} and T_{min} are all constants. It is noticeable that the spatial variation of wheat productivity is positively related to T_{min} but negatively related to T_{max}, which means that wheat productivity tends to increase spatially with higher T_{min} but lower T_{max}. Solar radiation also shows a positive effect on wheat productivity as an increase of 40.38 MJ/m^2 in *Rad* could result in an increase of 5206.53 kg/ha in wheat productivity.

3.3. Long-term change of wheat productivity in association with climate

Averaging across the NCP, for the period from 1960 to 2010, the standard deviation (*SD*) of regional wheat productivity is around 892 kg/ha, and the coefficient of variation (*CV* = *SD*/*Mean*) is around 0.13 implying rather low inter-annual variation of wheat production. For the same period, according to the result of a Mann-Kendall trend test (Kendall, 1975; Mann, 1945), it is found that there is a slight but not statistically significant increasing trend in the regional rain-fed wheat productivity in the NCP. As shown in Table 2, the increasing rate of regional wheat productivity is only around 4.70 kg/ha/a. Table 2 also shows the long-term trends of climate variables in the growing season averaging across the NCP, which includes *P*, T_{min}, T_{max}, *Rad* and aridity index (*AI*) in the growing season. For the period 1960 to 2010, no significant trend of precipitation is detected, but T_{min} is found to increase significantly while *Rad* is seen to decrease significantly. In practice, higher T_{min} could lead to higher wheat productivity. On the contrary, less solar radiation could result in lower wheat productivity in the NCP. The results imply that the stimulation effect owing to warming could have been offset by the reduction of solar radiation and therefore result in an insignificant change of wheat productivity in the NCP.

Spatially, the trend of wheat productivity varies significantly. As shown in Fig. 6, the long-term change rate of wheat productivity varies from −43.1–54.4 kg/ha/a across the NCP for the period 1960 to 2010. Among the 73 sites, 14 sites show noticeable reductions in productivity, and 20 sites experience unnoticeable reductions. Meanwhile, 39 sites show increasing trends, in which only one site has a statistically significant trend. It is recognized that the sites with relatively higher wheat productivity, which are mainly located in the southern and northeastern NCP, have been experiencing reductions in wheat productivity as a consequence of climate change. On the contrary, those sites located at the middle and northern part of NCP with relatively lower wheat yield have been experiencing upward trends in wheat productivity. The results suggest that the effect of climate change on wheat productivity varies among the climate regions (e.g. Chen et al., 2010; Yang et al., 2013). The spatial variance of the long-term trend of wheat productivity owing to climate change is determined by two underlying issues, i.e., the spatial difference in the climate trend and the different reaction of wheat growth to climate variables. To further

Table 2
Statistics of wheat productivity and related growing-season climate variables for NCP regional average. *Mean*, *SD* and *CV* are annual average, standard deviation and coefficient of variation; *MKZ* is the Z statistic in the Mann-Kendall trend test; trend exists at the significant level of 0.05 when absolute value of *MKZ* is higher than 1.96; *CR* is the change rate estimated by Mann-Kendall; R_p is the partial correlation coefficient between wheat productivity and the corresponding growing-season climate variables.

Statistics	*Yield*	T_{max}	T_{min}	*Rad*	*P*	*AI*
Mean	6685 kg/ha	14.1 °C	4.1 °C	3471 MJ/m^2	268 mm	3.10
SD	892 kg/ha	0.48 °C	0.55 °C	202 MJ/m^2	57 mm	0.80
CV	0.13	0.03	0.13	0.06	0.21	0.26
MKZ	0.36	1.63	**6.08**	**−6.08**	−0.04	−0.99
CR	4.70 kg/ha/a	0.01 °C/a	0.03 °C/a	−10.36 MJ/m^2/a	−0.03 mm/a	−0.01
R_p	1	−0.27	0.14	−0.14	0.65	NA

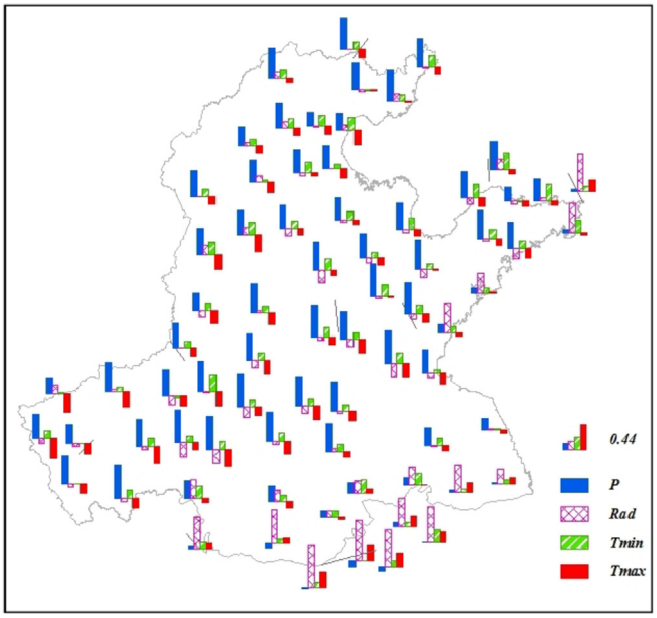

Fig. 7. Partial correlation coefficients between wheat productivity and growing-season climate factors for the period 1960–2010.

explore the spatial difference of the response of wheat productivity to climate change, the long-term trends (Fig. 6) of the dominant climate variables in the growing season are detected by the Mann-Kendall test; and the partial correlation analysis (Fig. 7) between wheat productivity and climate variables in the growing season is conducted for all sites across the NCP. The partial correlation analysis is preferred herein because it is capable of identifying the individual effects of each climate variable while eliminating the cross-correlation between them.

Fig. 7 shows the relationship between wheat productivity and four dominant climate factors in the growing season for each site as described by the partial correlation coefficient. It is found that variation of wheat productivity is positively related to change in precipitation across most sites in the semi-arid region, but insignificant negative relationship is found at five sites in the southern edge of the NCP, which belongs to the humid region ($AI < 1.5$). The close relation between precipitation and wheat productivity means that the growth of winter wheat is under a water constraint for most parts of the NCP. To improve wheat productivity across the NCP, therefore, one of the most effective measures is to promote and extend the application of irrigation. However, the results here are not being used to promote further increases in irrigation water in the region as over-withdrawal of groundwater for irrigation has caused critical environmental problems in the NCP (Mo et al., 2009). Given the scarcity of water resources, it is more important to improve irrigation efficiency via optimal irrigation scheduling, such as timely applications of irrigation based on crop requirements and soil conditions (Liang et al., 2011). In terms of the impact of precipitation change, as presented in Fig. 6, there is no significant trend with respect to precipitation across the NCP, which implies that the contribution of precipitation to wheat productivity change across the NCP is limited.

For the same period, a significant increase of T_{min} is found almost at all sites across the NCP (Fig. 6). Meanwhile, T_{max} shows a significant upward trend at 22 sites largely situated at the eastern coastal zone of the NCP (Fig. 6). As demonstrated at Fig. 7, positive correlations between wheat productivity and T_{min} are observed at most sites (except for 4 sites) of the NCP. Adversely, T_{max} is negatively related to productivity at almost all sites. The results indicate that, for most part of NCP, the increasing T_{min} could benefit wheat productivity as it could potentially alleviate frost damage during the growing season of the winter wheat (Sun et al., 2015), while higher T_{max} could harm wheat productivity since it would intensify the drought stress on wheat growth and grain formation. Especially, in the semi-arid area with AI greater than 1.5, although increasing T_{min} alleviates frost damage, more frequent drought stress at the reproductive stage could have induced wheat plant floret sterility (Tian et al., 2009). In the relatively wetter region as in the southern edge of the NCP, however, higher T_{max} could boost wheat growth owing to more available heat given sufficient water resources. It is worth noting that the warming climate could shorten the growth duration of current wheat, which leads to lower wheat productivity across the NCP. In adaption to a warming climate, cultivars with longer growing periods or those that are drought-resistant and tolerant of high temperatures would be better choices in the NCP. Alternatively, the cultivars with faster development rates and earlier flowering times that can extend the grain-filling duration might be adopted under the changing climate (Zhang et al., 2010).

Fig. 6 also shows that *Rad* decreases significantly at almost all sites across the NCP. In Fig. 7, the correlation between wheat productivity and solar radiation (*Rad*) in the growing season is found to be negative across 36 sites but most of them are not statistically significant (at the level of $\alpha = 0.1$), while remarkably a positive correlation is found at 16 sites. The sites with positive correlation are mostly located at the southern edge and eastern coastal region of the NCP and have a lower AI (< 2.0). At the humid southern edge, *Rad* is an influential factor controlling wheat productivity since higher *Rad* would further boost wheat development and grain formation owing to better soil moisture conditions. As a result, at the southern edge of the NCP, wheat productivity decreased concurrently with the decline of solar radiation (e.g. Chen et al., 2010). On the contrary, in the dry north, the decreasing solar radiation promotes wheat productivity to some extent since it could reduce the evaporation loss of soil water and consequently mitigate water stress. With the consideration of the close correlation between solar radiation with wheat productivity, particularly in the southern edge, the cultivars that could maintain higher photosynthesis rates under weak radiation might be top choices in wheat cropping for climate change adaptation.

4. Conclusions

Global food security over the next few decades will be under challenge owing to climate change and socio-economic development. China is one of the countries most affected thus by climate change and may experience serious reduction of crop yield if without effective climate change mitigation and adaptation strategies. The strategies rely deeply on the knowledge about the association between crop yield and climate. In this study, we have investigated the association across the North China Plain, which is known as the barn of China, for the period 1960–2010 with the application of the process-based agricultural model APSIM in combination with an empirical approach.

The results have shown that the annual winter wheat productivity generally decreases from southeast to northwest across the NCP. Overall, the spatial variation of wheat productivity is negatively related to daily maximum temperature but positively related to daily minimum temperature, solar radiation and precipitation. In the humid southern edge of NCP, too much rainfall in the growing season may result in wheat yield reduction. The spatial association between wheat yield and climate has been shown here to be useful to evaluate the productivity of the sites across the NCP even for those without any daily meteorological observations.

During the past 50 years (1960–2010), there has been no significant change of precipitation in the NCP. However, T_{min} has increased significantly while solar radiation has decreased significantly. As a consequence of climate change, though there is no significant trend in the rain-fed wheat productivity on average across the NCP, the southern edge and eastern coastal part of the NCP have been experiencing reductions of wheat productivity, while the northern part of the NCP has been experiencing an upward trend. For most parts of the NCP, the increasing T_{min} could benefit wheat productivity while increasing T_{max}

plays an adverse role. In the humid southern edge of the NCP, however, the increasing T_{max} and solar radiation could boost wheat growth as more energy is available and there is little constraint on water availability. In the drier north of the NCP, wheat productivity is mainly discounted by less precipitation.

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